A Time Series Approach for Soil Moisture Estimation

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ABSTRACT

Soil moisture is a key parameter in understanding the global water cycle and in predicting natural hazards. Polarimetric radar measurements have been used for estimating soil moisture of bare surfaces. In order to estimate soil moisture accurately, the surface roughness effect must be compensated properly. In addition, these algorithms will not produce accurate results for vegetated surfaces. It is difficult to retrieve soil moisture of a vegetated surface since the radar backscattering cross section is sensitive to the vegetation structure and environmental conditions such as the ground slope. Therefore, it is necessary to develop a method to estimate the effect of the surface roughness and vegetation reliably. One way to remove the roughness effect and the vegetation contamination is to take advantage of the temporal variation of soil moisture. In order to understand the global hydrologic cycle, it is desirable to measure soil moisture with one- to two-days revisit. Using these frequent measurements, a time series approach can be implemented to improve the soil moisture retrieval accuracy.

I. INTRODUCTION

Soil moisture is an important parameter in understanding the global hydrologic cycle that is an endless process linking water in the atmosphere, on the continents, and in the oceans. Knowledge of the land hydrosphere state is a key to understanding the global water and energy cycle. Soil moisture plays an important role in the interactions between the land surface and the atmosphere and the partitioning of precipitation into runoff and ground water storage. Therefore, soil moisture is a critical parameter needed in numerous Earth science areas and has significant practical applications such as predicting natural hazards.

Although soil moisture is a key parameter, it is not widely used due to the difficulty in measuring soil moisture accurately in a large area with sufficient spatial resolution. Most radar soil moisture algorithms are based on either experimental or numerical scattering data. The experimental data were typically collected using ground scatterometers. For the radar frequency, L-band (about 24cm wavelength) is desirable for measuring soil moisture since the vegetation contamination is less at this long wavelength.

For bare surfaces, polarimetric radar data have been used to provide multiple inputs to a soil moisture algorithm in order to estimate more than one surface parameter [1]. Typical surface parameters are soil moisture and surface roughness descriptors such as an rms height and a correlation length. In order to retrieve soil moisture accurately, the surface roughness effect must be compensated. One simple way to eliminate the surface roughness effect is to implement a time-series approach. If the surface roughness does not change in a short time period, soil moisture is the main source of the temporal variation of radar measurements. Using a relationship between radar measurements and soil moisture, accurate soil moisture information can be retrieved as long as the roughness does not change significantly. A similar approach can be used for vegetated surfaces even though the vegetation scattering model is much more complex. This time-series approach was successfully applied to the ERS data by Wolfgang Wagner and Klaus Scipal [2] to estimate a relative measure of soil moisture.

II. TIME SERIES SOIL MOISTURE MODELS

The dominant source of the soil moisture variation in time is a precipitation event. Therefore, a time series solution is effective in identifying precipitation events and estimating soil moisture for both bare and vegetated surfaces.

For bare surfaces, in order to relate the polarimetric parameters to soil moisture, we start with the first order Small Perturbation Method (SPM) given by

$$\sigma_{hhhh} \approx \left|\alpha_{hh}(\varepsilon,\theta)\right|^2 F(\lambda,\theta,h_{rms}) \qquad (1)$$

$$\sigma_{vvvv} \approx \left|\alpha_{vv}(\varepsilon,\theta)\right|^2 F(\lambda,\theta,h_{rms}) \qquad (2)$$

The SPM results are valid for bare surfaces with a small rms height. If $\left|\alpha_{hh}(\varepsilon,\theta)\right|^2$ and $\left|\alpha_{vv}(\varepsilon,\theta)\right|^2$ can be written as m_v^a [3], then

$$10\log_{10}(\sigma) \approx a\left[10\log_{10} m_v\right] + 10\log_{10}\left[F(\lambda,\theta,h_{rms})\right] \qquad (3)$$

Based on equation (3), a linear relationship exists between volumetric soil moisture and two co-polarized backscattering cross sections in the dB domain. Figure 1 shows the linear relationship (slope = 0.57) for $\left|\alpha_{hh}(\varepsilon,\theta)\right|^2$. A similar relationship (slope = 0.83) can be observed for $\left|\alpha_{vv}(\varepsilon,\theta)\right|^2$.

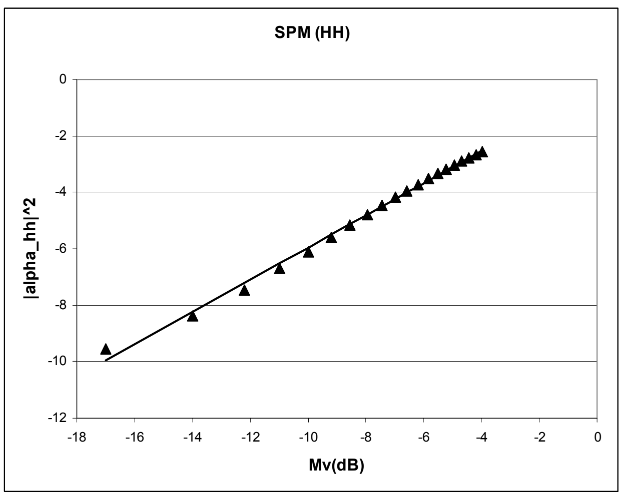

Fig. 1. Linear relationship between $\left|\alpha_{hh}(\varepsilon,\theta)\right|^2$ (triangles) and m_v (volumetric soil moisture) on a log-log scale at 40 degrees incidence angle. The volumetric soil moisture (m_v) value was varied from 2% to 40%.

The slope of the linear expression depends on the incidence angle as shown in Fig. 2. Notice that the vertical polarization measurement provides much larger dynamic range for bare surfaces.

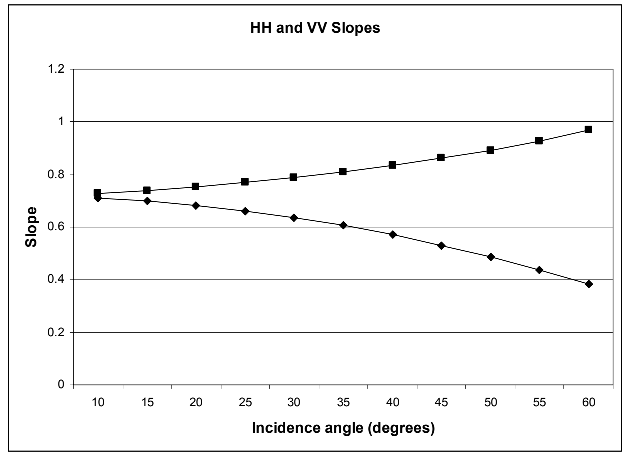

Fig. 2. Linear slopes of both H- (diamond) and V-polarizations (square) using SPM.

In order to understand the roughness effect, we used the first order tilted Bragg expressions shown in equations (4), (5), and (6)

$$\sigma_{vvvv} \approx \left[(1-\chi)\left|\alpha_{vv}\right|^2 + \chi\left|\alpha_{hh}\right|\left|\alpha_{vv}\right|\right] F_{TB}(\lambda,\theta,h_{rms}) \qquad (4)$$

$$\sigma_{hhhh} \approx \left[(1-\chi)\left|\alpha_{hh}\right|^2 + \chi\left|\alpha_{hh}\right|\left|\alpha_{vv}\right|\right] F_{TB}(\lambda,\theta,h_{rms}) \qquad (5)$$

where the roughness parameter is given by

$$\chi = \frac{2\left\langle h_y^2\right\rangle}{\sin^2\theta} \qquad (6)$$

and $\left\langle h_y^2\right\rangle$ is the azimuth slope variance. Under the tilted Bragg approximation, it was noticed that the linear slope changes as the surface roughness increases. For H-polarization, the slope increases as the roughness increases. For V-polarization, the slope decreases.

We also used IEM (Integral Equation Method) results to examine the linear relationship as shown in Fig. 3. The backscattering cross sections were calculated at L-band for bare surfaces characterized by a rms height of 0.75 cm and a correlation length of 12.5 cm. The incidence angle is 40 degrees. Notice that the results from IEM also show a linear relationship. The slope of the linear relationship is about 0.86 that is similar to the SPM result shown in Fig. 2.

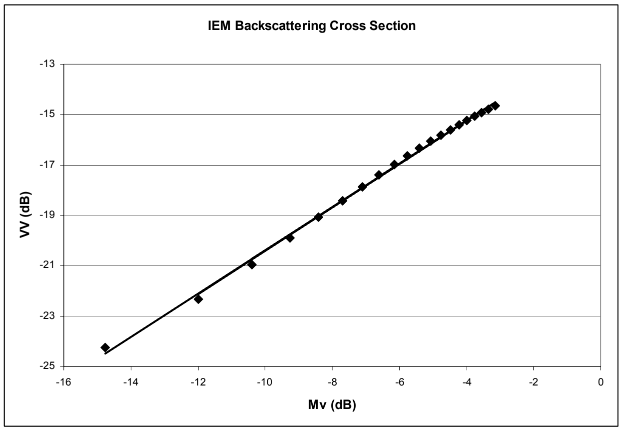

Fig. 3. Linear relationship between the backscattering cross section (vertical polarization) calculated using IEM and soil moisture on a log-log scale.

For vegetated surfaces, we used the polarimetric radar measurements from a corn field presented in [4]. This data set was acquired over the changing moisture and vegetation conditions during a growing season. In this case, a better linear relationship can be observed between the backscattering cross section (in dB) and soil moisture (in %). A similar result was reported in [5].

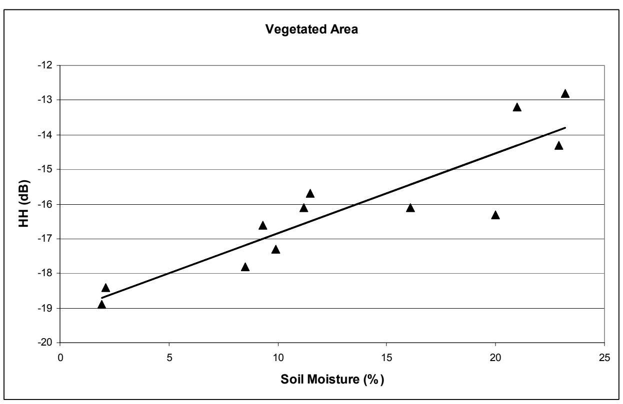

Fig. 4. Linear relationship between the backscattering cross section (in dB) and soil moisture (in %).

III. TIME SERIES RETRIEVAL ACCURACY

In order to use the linear model shown in the previous section for estimating soil moisture, we need the soil moisture information for at least two points. This reference information can be obtained from extreme soil moisture values (dry and wet) or existing polarimetric soil moisture algorithms.

We estimated the soil moisture retrieval accuracy under various error sources. In order to estimate soil moisture accurately (about 4% m_v error), the relative accuracy of radar measurements must be better than 0.5 dB. For these two reference soil moisture points, the soil moisture accuracy must be better than 4%.

For bare surfaces, more accurate results can be obtained using vertical polarization measurements since their dynamic range over varying soil moisture is large. However, for vegetated areas, horizontal polarization measurements provide more accurate soil moisture information. We speculate that the stronger double bounce term in the vegetation scattering model improves the soil moisture retrieval accuracy using horizontal polarization measurements. In addition, cross polarization measurements can be used for land classification.

ACKNOWLEDGMENT

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